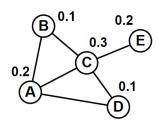
Final Exam (Graph Neural Networks –Fall 2023)

Full Name: Student ID:

1. Consider an undirected graph G of five nodes A, B, C, D, and E given in the following figure. Each node has initial features that are the numbers standing next to it (i.e., the initial feature of node 'A' is $h_A^{(0)} = 0.2$). According to GraphSAGE model with a AGGREGATE is a MEAN function, the feature of a node i at layer k can be updated as:

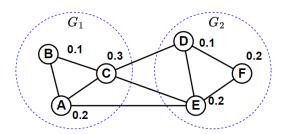


$$h_{N(i)}^{(k)} = \text{AGGREGATE}\left(\left\{h_u^{(k-1)}, \forall u \in N(i)\right\}\right)$$
$$h_i^{(k)} = \text{ReLU}\left(h_i^{(k-1)} \parallel h_{N(i)}^{(k)}\right)$$

where \parallel is a concatenation, ReLU(x) = max(0, x), N(i) is the neighbour nodes of node i.

- a) Calculate the feature of each node at k = 1.
- b) Calculate a graph-level embedding h_G by using a 'Mean' global pooling when k=1. **SOLUTIONS:**

2. Consider an undirected graph G of six nodes A, B, C, D, E and F given in the following figure. The graph G contains two cluster G₁ and G₂. Each node has initial features that are the numbers standing next to it. According to ClusterGCN model, the feature of a node *i* at layer *k* can be updated as:



$$\begin{split} h_{N(i)}^{(k)} &= \text{MEAN}\Big(\Big\{h_u^{(k-1)}, \forall u \in N(i), G_u = G_i\Big\}\Big)\\ h_i^{(k)} &= \text{ReLU}\Big(h_i^{(k-1)} \mid\mid h_{N(i)}^{(k)}\Big)\\ \text{where } \mid\mid \text{is a concatenation.} \end{split}$$

Calculate the output representations of all nodes at layer k = 1.

SOLUTIONS:

 $h_F^{(1)} = \text{ReLU}(h_F^{(0)} || h_{N(F)}^{(0)}) = Max(0, [0.2, 0.15]) = [0.2, 0.15]$

3. Given a graph with an adjacency matrix A and initial node feature matrix $H^{(0)}$ as follows:

$$A = \begin{bmatrix} 0 & 1 & 0 & 1 \\ 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \\ 1 & 0 & 1 & 0 \end{bmatrix} \qquad H^{(0)} = \begin{bmatrix} 1 \\ 0 \\ 2 \\ 1 \end{bmatrix}$$

Assume that the output of an GCNII model of all nodes at layer (k) can be calculated as:

$$H^{(k)} = \sigma \left[\left(\left(1 - \beta \right) I_n \right) \cdot \left(\left(1 - \alpha \right) \tilde{A} \cdot H^{(k-1)} + \alpha H^{(0)} \right) \right]$$

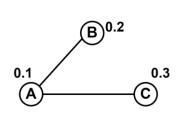
where $H^{(k)}$ denotes the output at layer k, \tilde{A} is the normalized matrix ($\tilde{A} = D^{-1}A$), I_n is the identity matrix, $\alpha = \beta = 0.5$, σ is a ReLU function ReLU(x) = max(0,x).

- a) Calculate \tilde{A} .
- b) Calculate the output representations at layer k = 1.

SOLUTIONS

$$\begin{split} \tilde{A} &= D^{-1}A = \begin{bmatrix} 0 & 0.5 & 0 & 0.5 \\ 0.5 & 0 & 0.5 & 0 \\ 0 & 0.5 & 0 & 0.5 \\ 0.5 & 0 & 0.5 & 0 \end{bmatrix} \\ H^{(k)} &= \sigma \Big[\Big((1 - \beta) I_n \Big) \Big((1 - \alpha) \tilde{A} \cdot H^{(k-1)} + \alpha H^{(0)} \Big) \Big] \\ \tilde{A} \cdot H^{(0)} &= \begin{bmatrix} 0 & 0.5 & 0 & 0.5 \\ 0.5 & 0 & 0.5 & 0 \\ 0 & 0.5 & 0 & 0.5 \\ 0.5 & 0 & 0.5 & 0 \end{bmatrix} \cdot \begin{bmatrix} 1 \\ 0 \\ 2 \\ 1 \end{bmatrix} = \begin{bmatrix} 0.5 \\ 1.5 \\ 0.5 \\ 1.5 \end{bmatrix} \\ I_n &= \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \\ \Big[\Big((1 - \alpha) \tilde{A} \cdot H^{(k-1)} + \alpha H^{(0)} \Big) \cdot \Big((1 - \beta) I_n \Big) \Big] \\ &= \begin{bmatrix} 0.5 \\ 0.5 \\ 0.5 \\ 0.5 \\ 1.5 \end{bmatrix} - 0.5 \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \cdot \begin{bmatrix} 0.5 \\ 1.5 \\ 0.5 \\ 1.5 \end{bmatrix} + 0.5 \begin{bmatrix} 1 \\ 0 \\ 2 \\ 1 \end{bmatrix} = 0.5 \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} 0.5 \begin{bmatrix} 1.5 \\ 1.5 \\ 2.5 \\ 2.5 \end{bmatrix} = 0.25 \begin{bmatrix} 1.5 \\ 1.5 \\ 2.5 \\ 2.5 \end{bmatrix} = \begin{bmatrix} 0.375 \\ 0.625 \\ 0.625 \end{bmatrix} \\ H^{(k)} &= \sigma \begin{bmatrix} 0.375 \\ 0.625 \\ 0.625 \\ 0.625 \end{bmatrix} = \begin{bmatrix} 0.375 \\ 0.625 \\ 0.625 \\ 0.625 \end{bmatrix} \end{split}$$

4. Consider an undirected graph G of three nodes A, B, and C given in the following figure. Each node has initial features that are the numbers standing next to it (i.e., the initial feature of node 'A' is $h_A^{(0)} = 0.1$). According to GAT model, the weight matrix W is randomly initialized as [0.5]. The feature of node 'i' at layer (k) can be updated as:



$$h_i^{(k)} = \sigma \left(\sum_{m \in N(i)} \alpha_{im} W h_m \right)$$

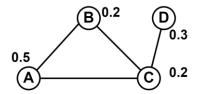
where:
$$\alpha_{im} = \frac{e_{im}}{\sum_{k \in N(i)} e_{ik}}$$
, and $e_{im} = \sigma(\text{MEAN}(Wh_i, Wh_m))$

 σ is a ReLU function ReLU(x) = max(0, x).

- a) Calculate the attention coefficients e_{AB} and e_{AC}
- b) Calculate the feature of node 'A' at k = 1.

SOLUTIONS:

5. Consider an undirected graph G of four nodes A, B, C, and D given in the following figure. Each node has initial features that are the numbers standing next to it (i.e., the initial feature of node 'A' is $h_A^{(0)} = 0.5$). According to GIN model, the parameter is a fixed scalar $\varepsilon = 0.5$, the feature of a node i at layer k can be updated as:



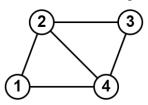
$$h_i^{(k)} = \left(1 + \varepsilon\right) \cdot h_i^{(k-1)} + \sum_{j \in N(i)} h_j^{(k-1)}$$

- a) Calculate the feature of each node at k = 1.
- b) Calculate a graph-level embedding h_G by using a 'Max' global pooling when k=1.

SOLUTIONS:

$$\begin{split} h_i^{(k)} &= \left(1+\varepsilon\right) \cdot h_i^{(k-1)} + \sum_{j \in N(i)} h_j^{(k-1)} \\ h_A^{(1)} &= \left(1+\varepsilon\right) \cdot h_A^{(0)} + \left(h_B^{(0)} + h_C^{(0)}\right) = \left(1+0.5\right) * 0.5 + \left(0.2+0.2\right) = 1.15 \\ h_B^{(1)} &= \left(1+\varepsilon\right) \cdot h_B^{(0)} + \left(h_A^{(0)} + h_C^{(0)}\right) = \left(1+0.5\right) * 0.2 + \left(0.5+0.2\right) = 1 \\ h_C^{(1)} &= \left(1+\varepsilon\right) \cdot h_C^{(0)} + \left(h_A^{(0)} + h_B^{(0)} + h_D^{(0)}\right) = \left(1+0.5\right) * 0.2 + \left(0.5+0.2+0.3\right) = 1.3 \\ h_D^{(1)} &= \left(1+\varepsilon\right) \cdot h_D^{(0)} + \left(h_C^{(0)}\right) = \left(1+0.5\right) * 0.3 + \left(0.2\right) = 0.65 \\ h_G^{1} &= MAX\left(h_A^{(1)}, h_B^{(1)}, h_C^{(1)}, h_D^{(1)}\right) = 1.15 \end{split}$$

6. Consider an undirected graph G of four nodes given in the following figure. The Random Walk Positional Encoding, which is used in SAT model, of a node *i* can be calculated as:



$$p_i^{\mathit{RWPE}} = \left[\tilde{A}_{ii}, \tilde{A}_{ii}^2, \ldots, \tilde{A}_{ii}^k \right]$$

where \tilde{A} is the normalized adjacency matrix $\tilde{A} = D^{-1}A$, \tilde{A}^k is the k-step transition probability matrix $\tilde{A}^k = \underbrace{\tilde{A} \cdot \tilde{A} \cdots \tilde{A}}_{k}$. Calculate the positional encoding of each node at k = 2.

SOLUTIONS

$$\tilde{A} = D^{-1}A = \begin{bmatrix} 0 & 0.5 & 0 & 0.5 \\ 0.33 & 0 & 0.33 & 0.33 \\ 0 & 0.5 & 0 & 0.5 \\ 0.33 & 0.33 & 0.33 & 0 \end{bmatrix}$$

$$\tilde{A}^2 = \tilde{A}\tilde{A} = \begin{bmatrix} 0 & 0.5 & 0 & 0.5 \\ 0.33 & 0 & 0.33 & 0.33 \\ 0 & 0.5 & 0 & 0.5 \\ 0.33 & 0.33 & 0.33 & 0 \end{bmatrix} \begin{bmatrix} 0 & 0.5 & 0 & 0.5 \\ 0.33 & 0 & 0.33 & 0.33 \\ 0 & 0.5 & 0 & 0.5 \\ 0.33 & 0.33 & 0.33 & 0 \end{bmatrix} = \begin{bmatrix} [0.33, 0.16, 0.33, 0.16], \\ [0.11, 0.44, 0.11, 0.33], \\ [0.33, 0.16, 0.33, 0.16], \\ [0.11, 0.33, 0.11, 0.44] \end{bmatrix}$$

$$p_A^{RWPE} = \left[\tilde{A}_{11}, \tilde{A}_{11}^2\right] = [0, 0.33]$$

$$p_B^{RWPE} = \left[\tilde{A}_{22}, \tilde{A}_{22}^2\right] = [0, 0.44]$$

$$p_C^{RWPE} = \left[\tilde{A}_{33}, \tilde{A}_{33}^2\right] = [0, 0.33]$$

$$p_D^{RWPE} = \left[\tilde{A}_{44}, \tilde{A}_{44}^2\right] = [0, 0.44]$$